11-2018

Early Warnings for State Transitions

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Rangeland Ecology & Management 71 (2018) 659–670

Contents lists available at ScienceDirect

Rangeland Ecology & Management

journal homepage: http://www.elsevier.com/locate/rama

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ARTICLE INFO

Article history:
Received 4 November 2017
Received in revised form 18 April 2018
Accepted 30 April 2018

Key Words:
early warning
rangeland monitoring
regime shift
resilience
spatial regimes
state-and-transition model

ABSTRACT

New concepts have emerged in theoretical ecology with the intent to quantify complexities in ecological change that are unaccounted for in state-and-transition models and to provide applied ecologists with statistical early warning metrics able to predict and prevent state transitions. With its rich history of furthering ecological theory and its robust and broad-scale monitoring frameworks, the rangeland discipline is poised to empirically assess these newly proposed ideas while also serving as early adopters of novel statistical metrics that provide advanced warning of a pending shift to an alternative ecological regime. We review multivariate early warning and regime shift detection metrics, identify situations where various metrics will be most useful for rangeland science, and then highlight known shortcomings. Our review of a suite of multivariate-based regime shift/early warning indicators provides a broad range of metrics applicable to a wide variety of data types or contexts, from situations where a great deal is known about the key system drivers and a regime shift is hypothesized a priori, to situations where the key drivers and the possibility of a regime shift are both unknown. These metrics can be used to answer ecological state-and-transition questions, inform policymakers, and provide quantitative decision-making tools for managers.

Introduction

Rangeland evaluation and monitoring have been intertwined with advances in ecological theory since the early 20th century (Clements, 1916; Sampson, 1917, 1919). Early successional theory (Clements, 1916) motivated evaluations that linked rangeland degradation to shifts in vegetation following an orderly successional trajectory (Sampson, 1917, 1919; West, 2003). Models of successional retrogression, introduced shortly after coordinated federal monitoring efforts, attempted to provide solutions to the deleterious grazing practices and unrestricted livestock use contributing to widespread soil erosion and increasing dominance of species with lower forage value (Dyksterhuis, 1949). The successional retrogression model dominated rangeland management for 50 yr, until advances in alternative state theory and the inability of the succession-retrogression model to explain many changes in rangelands prompted a shift to the state-and-transition modeling framework introduced by Westoby et al. (1989). State-and-transition models are one of the most commonly used management frameworks in the world (i.e., USDA Ecological Site Descriptions State-and-Transition Models; Briske et al., 2006), but capture only a small component of the complex, adaptive behaviors that ultimately determine why ecosystems persist or, alternatively, change form (Twidwell et al., 2013).

New concepts have emerged in theoretical ecology with the intent to not only quantify complexities in ecological change inherently unaccounted for in state-and-transition models but to also help applied ecologists "turn back from the brink" prior to reaching regime shifts (i.e., state transitions; definitions provided in Table 1) in ecological systems (Biggs et al., 2009). These concepts center around the theory that ecological systems can exist in multiple, dynamic basins of attraction (i.e., regimes), fundamentally similar to "states" of the state-and-transition models (Briske et al., 2008; Scheffer, 2009). Overwhelming disturbance(s) can push a regime past a threshold and into an alternate regime (Scheffer and Carpenter, 2003; Briske et al., 2005; Folke et al., 2004). Systems that have undergone shifts to regimes with lower ecosystem service potential (e.g., desertification or woody encroachment of rangelands) may exhibit hysteretic behavior; that is, restoration to

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https://doi.org/10.1016/j.rama.2018.04.012
1550-7424/

Table 1
Glossary of terms.

Term	Definition
Early Warning Indicator	"hypothesized to signal the loss of system resilience and have been shown to precede critical transitions in theoretical models, paleoclimate times series, and in laboratory as well as whole lake experiments" (Gsell et al., 2016)
Hysteresis	"in which the forward and backward switches occur at different critical conditions" (Scheffer et al., 2001) "the path out is not the same as the path in" (Angeler and Allen, 2016)
Regime	"configuration in terms of abundance and composition, function and process, of a system...The terms state and regime are often used interchangeably. However, regime specifically refers to the processes and feedbacks that confer dynamic structure to a given state of a system" (Angeler and Allen, 2016)
Regime Shift	"conspicuous jumps from one rather stable [regime] to another" (Scheffer et al., 2001) "Sudden shifts in ecosystems, whereby a threshold is passed and the core functions, structure, and processes of the new regime are fundamentally different from the previous regime and hysteresis is present." (Scheffer and Carpenter, 2003)
Regime Shift Metric	"statistical metrics of system resilience [that] have been hypothesized to provide advance warning of sudden shifts in ecosystems" (Gsell et al., 2016)
State	"The 'state' of a system at a particular instant in time is the collection of values of the 'state' variables at that time...the term 'state' is loosely used to describe a characteristic of the system, rather than its state. For example, the lake is in a eutrophic 'state', or the rangeland is in a shrub-dominated 'state'." (Walker et al., 2002)
State-and-Transition Models	"..a framework to accommodate a broader spectrum of vegetation dynamics on the basis of managerial, rather than ecological, criteria… initially designed for application on rangelands characterized by discontinuous and nonreversible vegetation dynamics." Based on "1) potential alternative vegetation states [at] a site, 2) potential transitions between vegetation states, and 3) recognition of opportunities to achieve favorable transitions and hazards to avoid unfavorable transitions between vegetation states" (Briske et al., 2005)
State Variable	Biotic and abiotic system features that define and contrast system states. State variables can be "driving state variables" of system states (i.e., sufficient changes in driving state variables are known to alter system states) or simply indicative of system state (Walker et al., 2002).
Threshold	"Thresholds are equivalent to tipping points and may be detected as discontinuities or bifurcation points in complex systems" (Angeler and Allen, 2016)

the previous regime would require more effort than if it had been initiated prior to the regime shift, or the restoration would be practically infeasible (Scheffer et al., 2001; Folke et al., 2004; Angeler and Allen, 2016). Using metrics that signal early warning indicators (EWIs) and avoid regime shifts that are undesirable have therefore become a central pursuit in ecology (Brock and Carpenter, 2006, 2012; Andersen et al., 2009; Dakos et al., 2012), especially for known regime changes that exhibit strong hysteretic behavior. Theoretical ecologists have explored the behavior of state variables in systems on the cusp of regime shifts or where regime shifts were known a priori (Mantua, 2004; Carpenter et al., 2011). Much work has been done to assess early warning signals of regime shifts with univariate data and simple model systems (Hastings and Wysham, 2010; Burthe et al., 2016); however, univariate indicators may not capture the true complexity of ecosystem change possible with multivariate methods (Rodionov, 2004; Allen and Holling, 2008; Spanbauer et al., 2014; Eason et al., 2016).

The rangeland discipline, given its emphasis on long-term multivariate experimentation and monitoring programs that occur across multiple spatial and temporal scales, is poised to uniquely contribute to the science of early warnings and regime shifts in ecology. Theoretical ecology will benefit from the myriad of multivariate monitoring data available in rangelands to continue the tradition in rangelands of empirically testing new ideas associated with ecological assembly (Briske et al., 2005). The rangeland discipline will also benefit from merging convergent theoretical ecology concepts and techniques aimed at quantifying state transitions and providing a quantitative basis for making decisions in rangeland management (Allen et al., 2016; Angeler and Allen, 2016). But despite the applicability of early warning and regime shift theory to rangeland science, evidence suggests that rangeland science is lagging in the assessment of theoretical indicators used for regime shift prediction (Table 2). To date, most rangeland research has focused on qualitative assessments of state transitions, as opposed to quantitative and predictive metrics (Bashari et al., 2008; Bestelmeyer et al., 2009; Twidwell et al., 2013; see Table 2).

In this paper, we review and discuss multivariate metrics used to detect early warnings and regime shifts along with their utility in rangeland evaluation and monitoring. We focus on multivariate metrics with potential utility for detecting rangelands in transition, as opposed to univariate indicators, because the rangeland discipline has a long history of multivariate data inventory and monitoring, and comprehensive reviews of univariate metrics already exist that can guide rangeland specialists (e.g., Dakos et al., 2012). For each metric, we review the conceptual foundation leading to its proposed use as an early warning indicator of system-level change, highlight known shortcomings, and identify specific situations where each metric will be most useful for rangeland science, monitoring, and management. A suite of multivariate-based early warning and regime shift indicators were reviewed in this paper and provide a broad range of potential metrics applicable to a wide variety of data types and contexts—from situations where a great deal is known about the key system drivers and a regime shift is a priori hypothesized, to situations where the key drivers and the possibility of a regime shift are both unknown. We then provide three examples that showcase the potential utility of these metrics to future pursuits in rangeland science and management.

Literature Review and Methodology

We conducted a formal review using Web of Science to compile different multivariate metrics used for early warning and regime shift detection (Thompson Reuters Corporation, 2018; accessed on January 2016–June 2016). Accordingly, we used the following search terms: "Regime Shift AND Multivariate AND Each Metric Type".

We found 70 articles that used multivariate early warning and regime shift metrics in ecological studies. In these articles, we found 10 unique metrics, with the number of articles using each metric varying from 1 to 14 (Average Standard Deviates = 4, Conditional Probability Analysis = 1, Detrended Correspondence/Detrended Canonical Correspondence Analysis = 11, Discontinuity Analysis = 4, Fisher Information = 14, Generalized Modeling = 2, Intervention Analysis/Autoregressive Moving Averages = 5, Redundancy Analysis-distance–based Moran's Eigenvector Map/Asymmetric Eigenvector Map = 11, Sequential T-test Analysis of Regime Shifts = 14, Vector Autoregressive Model = 4). Three metrics had been tested as EWI metrics (Conditional Probability Analysis, Discontinuity Analysis, and Fisher Information), and the rest were regime shift detection metrics that have the potential to be or have been proposed as EWI metrics. Thus, we hereafter distinguish between "tested" and "proposed" EWI metrics. The earliest application of multivariate EWI metrics was in the early 1990s (Ebbesmeyer et al., 1991), and their use sharply increased beginning in the early 2000s (Thompson Reuters Corporation, 2018). Most studies we found used multivariate EWI metrics for time-series and aquatic system applications (Kirkman et al., 2015; Mantua, 2004), with only two studies using EWI metrics to detect regime shifts in space or terrestrial systems (Zurlini et al., 2014; Sundstrom et al., 2017).

To assist in the appropriate selection and application of multivariate EWI metrics in rangeland applications, we categorized metrics hierarchically according to their assumptions and data type requirements (Fig. 1) and organized the review accordingly. The primary division

Table 2
Literature review[1] of the total number of papers and the percentage using a quantitative metric[2] for early warning and regime shift detection in Rangeland Ecology & Management and other journals in the discipline.

Search term	In the journal of Rangeland Ecology & Management	In other journals in the discipline with the additional search term:	
		Rangeland	Ecology
State and Transition	147 (21%)	2 250 (30%)	3 450 (27%)
Alternative States	36 (31%)	953 (32%)	5 690 (30%)
State Transition	24 (17%)	580 (35%)	8 470 (30%)
Early Warning	18 (17%)	5 340 (26%)	17 500 (71%)
Regime Shift	7 (29%)	672 (42%)	110 000 (46%)
Early Warning Indicator	2 (0%)	87 (61%)	1 000 (42%)
Spatial Regime	0 (0%)	9 (33%)	310 (68%)

[1] Search returns were based on a formal review in Google Scholar. Values given in the table represent the sum of all search returns. Values in parentheses represent the percentage (%) of search returns including a quantitative metric.
[2] Quantitative metrics considered in our search include: autocorrelation, autoregressive model, autoregressive moving averages, average standard deviates, BDS test, coefficient of variation, conditional heteroscedasticity, conditional probability analysis, detrended canonical correspondence analysis, detrended correspondence analysis, detrended fluctuation analysis indicator, discontinuity analysis, fisher information, generalized modeling, intervention analysis, kurtosis, return rate, sequential T-test analysis of regime shifts, skewness, spectral density, spectral exponent, spectral ratio, standard deviation, and vector autoregressive modeling.

lies in whether driving state variables are known or unknown for the system in question (Table 3), and whether a relatively small (i.e., limited) or a relatively large (i.e., unlimited) number of state variables have been measured (Fig. 1). The second division separates metrics by whether they require the spatial or temporal "location" of a regime shift to be hypothesized a priori (Fig. 1). The tertiary division splits metrics by specific data type requirements (Fig. 1).

Synthesis of Metrics

Known Driving State Variables/Limited Number of State Variables

Metrics in this division (known/limited) share two assumptions: driving state variables are known, and driving state variables interact with each other (Fig. 1). Known/limited metrics all use regression-like methods, estimate coefficients, and have implicit significance tests

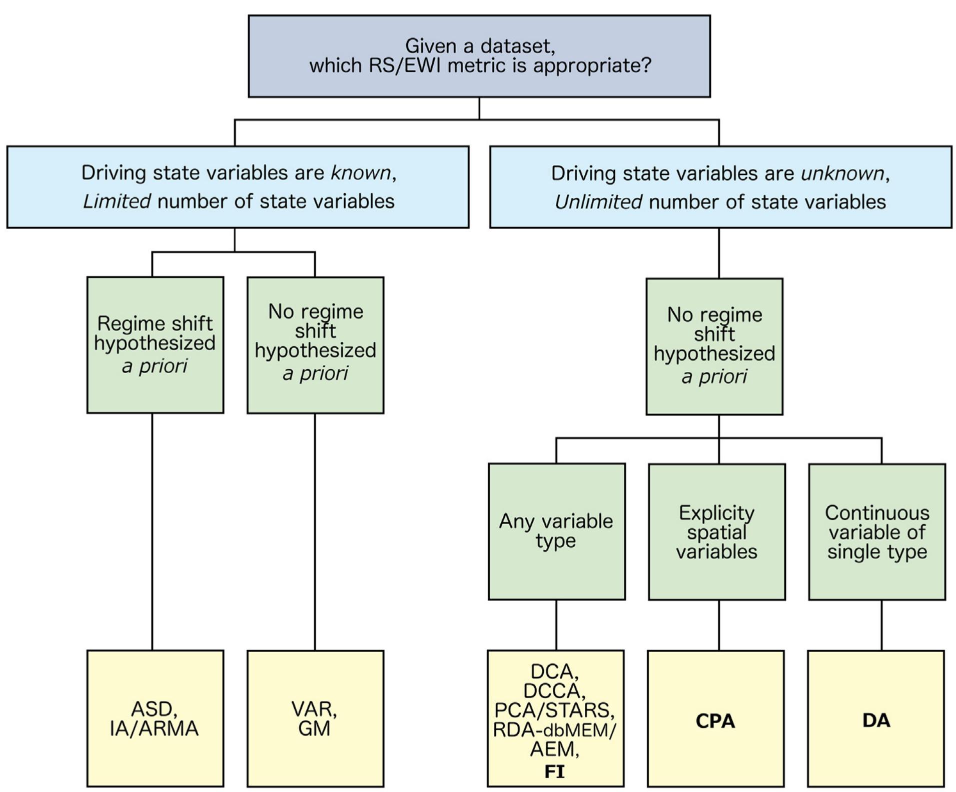

Figure 1. A flowchart for determining which multivariate metrics for regime shift/early warning detection are appropriate for a given set of state variables. “Limited” state variables indicates those metrics are suitable for relatively small number of input variables, and “known drivers” means that the input state variables represent known fundamental influences on system state. The lowest tier lists appropriate metrics for a given data type. Metrics in bold have been tested as early warning indicators of regime shifts. Metrics not in bold have been proposed as early warning metrics but only tested as regime shift indicators. RS indicates proposed early warning indicator; EWI, tested early warning indicator; ASD, average standard deviates; IA/ARMA, intervention analysis/autoregressive moving averages; VAR, vector autoregression; GM, generalized modeling; DCA, detrended correspondence analysis; DCCA, detrended canonical correspondence analysis; PCA/STARS; principal components analysis/sequential T-test analysis of regime shifts; RDA-dbMEM/AEM, redundancy analysis; FI, Fisher information; CPA, conditional probability analysis; DA, discontinuity analysis.

Table 3
Questions and situational examples for determining when using regime shift/early warning indicator metrics (EWI metrics) could be appropriate. For each question/situation, the "Why" and "Why not" columns provide positive and negative support, respectively, for the use of EWI metrics.

Should I use Early Warning Indicator metrics...	Why?	Why *not*?
System Considerations		
If hysteresis *is* present or likely?	• EWI metrics can allow management to prevent known or unknown imminent regime shifts. • Restoration of desirable states will be very costly or infeasible.	• There is extensive knowledge of system drivers and hysteresis. Thus, applying finances, time, and effort to preventative management is more beneficial.
If hysteresis *is not* present or likely?	• Restoration of desirable states, although possible or simple, will still be very costly.	• Same as above. • The cost to restore the desirable state is low.
Research Question Considerations		
While actively experimenting with thresholds or regime shifts?	• EWI metrics can quantitatively identify when/where thresholds or regime shifts occur. • Some EWI metrics can identify and rank relative influences of driving state variables (see Fig. 1).	• Experimentation on thresholds could cause catastrophic or expensive consequences, so EWI metrics are not useful or advisable. • Early warning may not be necessary; simply identifying regime shifts (e.g., with proposed EWI or regime shift detection metrics) may be sufficient.
While passively monitoring state variables?	• EWI metrics can provide early warnings for unknown or unforeseen regime shifts. • EWI metrics can provide an estimate of the typical range of variability in a state.	• There are other statistical metrics or procedures in place.
To identify historic thresholds or regime shifts?	• Many EWI metrics have been used extensively to identify historic thresholds and regime shifts. • EWI metrics can provide quantitative and qualitative evidence of the present/absence of thresholds and regime shifts. • Some EWI metrics have explicit significance tests and can provide levels of confidence (see Fig. 1).	• Early warning may not be necessary; simply identifying regime shifts (e.g., with proposed EWI or regime shift detection metrics) may be sufficient. • Some EWI metrics produce conflicting results when identifying historic regime shifts, so choosing the most appropriate metric can be challenging.
To detect spatial regimes?	• Some EWI metrics are amenable to detecting spatial regimes. • There is sufficient spatial data of the appropriate type to run EWI metrics amenable to detecting spatial regimes (see Fig. 1).	• Data type requirements are not met for EWI metrics suitable for detecting spatial regimes.
At any spatiotemporal scale?	• Some EWI metrics are amenable to detecting spatial and temporal regimes. • There is sufficient spatial and temporal data of the appropriate type to run EWI metrics.	• Data type requirements are not met for EWI metrics suitable for detecting spatiotemporal regimes.
Data Availability Considerations		
If long-term temporal monitoring data is available?	• Many EWI metrics were designed and have been well-studied in temporal contexts. • Long-term temporal data can provide more accurate portrayals of the typical range of variability in a state. This in turn can increase the accuracy of EWI metrics. • Historic thresholds and regime shifts can be identified, providing insight into potential regime shift hazards in the future.	• There is extensive knowledge of system drivers and hysteresis. Thus, applying finances, time, and effort to preventative management is more beneficial.
If only spatial data is available?	• Some EWI metrics can use explicitly spatial data to detect early warnings of regime shifts (see Fig. 1). • Some EWI metrics can use spatial data to identify spatial ecological regimes.	• Patterns may not be detectable with only one point in time.
If driving state variables are known?	• Some EWI metrics are designed for detecting thresholds or regime shifts with known driving state variables (see Fig. 1). • Knowing driving state variables may increase the performance of EWI metrics and allow more accurate and earlier regime shift detection.	• Monitoring known driving state variables may suffice for detecting imminent regime shifts and prioritizing management.
Social or Policy Considerations		
If social, policy, or legal concerns require confirmation of thresholds or regime shifts?	• EWI metrics can provide quantitative and qualitative evidence of the presence/absence of thresholds and regime shifts. • Policy or law mandates use of particular conceptual frameworks (e.g., state-transition models, ecological site descriptions) that would benefit from inclusion of quantitative metrics. • Some EWI metrics have explicit significance tests and can provide levels of confidence (see Fig. 1).	• Available data are insufficient or not appropriate to detect early warning and regime shifts at the scale necessary to guide policy or to avoid misinterpretation and misuse. • There is extensive knowledge of system drivers and hysteresis, so applying finances, time, and effort for preventative management is less of a priority than focusing on sociopolitical constraints.

(e.g., Solow and Beet, 2005; Lade and Gross, 2012), making them similar to nonlinear threshold modeling techniques (Sasaki et al., 2008). For these metrics, the regime is defined by modeling the interactions and variability amongst the chosen state variables, and a regime shift is detected when the behavior of state variables deviate significantly from a "typical" range at a given level of confidence (Gal and Anderson, 2010; Lade et al., 2013). Two of the known/limited metrics require a priori hypotheses of regime shift locations (Average Standard Deviates, Intervention Analysis/Autoregressive Moving Averages), and two known/limited metrics do not require a priori regime shift hypotheses (Vector Autoregression, Generalized Modeling). Known/limited metrics that do not require a regime shift to be hypothesized a priori can potentially provide early warnings if trends in state variable behavior approach the given confidence limit (Ives and Dakos, 2012).

These metrics can provide detailed quantitative and statistically rigorous results, but they require substantial system-specific a priori knowledge (Rudnick and Davis, 2003; Gal and Anderson, 2010). Major benefits of known/limited metrics include: 1) their ability to assess the validity of regime shifts and early warnings via null hypothesis tests and information theoretic approaches and 2) their ability to estimate the directionality and relative importance of the chosen driving state variables via coefficient estimation (Gal and Anderson, 2010; Lade and Gross, 2012). Because known/limited metrics assume driving state variables are known, correctly selecting state variables is essential

(Solow and Beet, 2005). Not including major driving variables or analyzing irrelevant variables could produce biased estimates or fail to detect regime shifts (Hare and Mantua, 2000). Additionally, overly conservative confidence requirements or biased estimates of "typical" ranges of state variable behavior may cause regime shift detection to lag (Ives and Dakos, 2012).

Regime Shift Hypothesized a Priori

Average Standard Deviates

Average Standard Deviates (ASD), developed by Ebbesmeyer et al. (1991), is a proposed EWI metric that focuses on identifying significant regime shifts using the magnitude of change in multiple time series records between pre- and post-a priori identified regime shift dates. Hare and Mantua (2000), Rudnick and Davis (2003), and Mantua (2004) summarize the methods in detail. Regime shifts are considered significant if the sign of standard deviates in all years is the same within each "half record" (designated by the location of the a priori identified step change) but opposite between half records, and no value is within a standard error of zero. This method has been strongly contested by Rudnick and Davis (2003), who remark on how it is designed to specifically create a step change and is highly sensitive to false positives when there is noise in the data. Mantua (2004) suggests an alternative method to mitigate this weakness, but to our knowledge, this has not been assessed within ecological regime shift literature. As of this review, ASD has be used solely in marine environments (Mantua, 2004).

Intervention Analysis/Autoregressive Moving Averages

Intervention analysis (IA; Wei, 1994) combined with autoregressive moving averages (ARMA) is a paired method for detecting significant changes in the mean of state variables in a time series while accounting for temporal autocorrelation (Mantua, 2004; Andersen et al., 2009). Together, intervention analysis and autoregressive moving average models (IA/ARMA) have been used to estimate the significance and magnitude of regime shifts in time series data (Gedalof et al., 2001). IA/ARMA requires either a priori knowledge of the regime shift (intervention) or an estimate of the temporal location of the shift, which can be identified by visual inspection of the time series data (Mantua, 2004). Intervention analysis is a method for confirming the presence of a regime shift on time series data, and ARMA is used in combination with IA when temporal autocorrelation is present or suspected in the data. Although IA accounts for stochastic noise, it may provide more useful knowledge about a system when using detrended data (Mantua, 2004).

No Regime Shift Hypothesized a Priori

Vector Autoregressive Model

Vector Autoregressive Modeling (VAR) models interactions between state variables and estimates coefficients much like a least squares regression (Mantua, 2004) and identifies regime shifts as switches from locally steady states in fitted values (Gal and Anderson, 2010). A parametric bootstrapping technique can determine statistical significance of changes in fitted values, and Markov-switching techniques can be added (Gal and Anderson, 2010). VAR has been applied to time-series data in aquatic systems and simulated data (Mantua, 2004; Solow and Beet, 2005; Gal and Anderson, 2010; Ives and Dakos, 2012). VAR can detect unknown (not hypothesized a priori) regime shifts and accounts for autocorrelation between variables and observations (Ives and Dakos, 2012). VAR cannot detect a regime shift in the first or last observation of a time-series, potentially causing lagged early warnings of regime shifts (Gal and Anderson, 2010). However, fitted values approaching the limit of the typical range of variability in a system could still provide an early warning signal (Ives and Dakos, 2012).

Generalized Modeling

Introduced by Lade and Gross (2012), generalized modeling (GM) as a proposed EWI metric creates dynamical functions to describe each variable and their interactions with other variables. Across a macroscopic time-scale, certain variables are assumed to change rapidly and stochastically around a locally stable state ("fast" variables), whereas others change gradually ("slow variables"). GM detects early warnings or regime shifts when eigenvalues in the "fast" variables shift away from their locally stable state (Lade and Gross, 2012). The GM metric is advantageous in that it requires relatively few time-series data points to robustly detect early warnings or regime shifts (Lade and Gross, 2012; Lade et al., 2013), and it can account for stochastic fluctuations in fast variables (Lade and Gross, 2012). However, high levels of noise in fast variables are known to decrease the accuracy of regime shift detection (Lade and Gross, 2012). Although GM has received little rigorous statistical testing in ecology, it shares many potential applications with the VAR metric (Lade and Gross, 2012).

Known OR Unknown Driving State Variables/Unlimited Number of State Variables

Overall, metrics in this division (unknown/unlimited) have fewer assumptions than the previous division (Angeler and Johnson, 2012; Spanbauer et al., 2016; Fig. 1). They do not require a priori knowledge about which state variables drive system form and function (although known driving state variables can be used), can readily accept an unlimited number of state variable inputs, and do not require a priori hypotheses of the spatial or temporal locations of regime shifts (Rodionov, 2004; Carstensen et al., 2013; Eason et al., 2016; Sundstrom et al., 2017; Zurlini et al., 2014). However, a few unknown/unlimited metrics have specific data type requirements, which produce tertiary divisions (Fig. 1). Metrics that accept any type or combination of state variables (Sequential T-test Analysis of Regime Shifts, Detrended Correspondence Analysis, Detrended Canonical Correspondence Analysis, Redundancy Analysis/distance-based Moran Eigenvector Maps or Asymmetric Eigenvector Maps, Fisher Information) define regimes by condensing state variables into a single value as a series of data points (e.g., a time-series, a spatial transect). These values fall within a stable range of variability, and regime shifts occur when values exceed a predetermined range of variability (e.g., Karunanithi et al., 2011; Baho et al., 2014). Discontinuity analysis, identifies gaps, or scale-breaks, in continuous, rank-ordered data of a single type (Allen and Holling, 2008). Finally, Conditional Probability Analysis requires explicitly spatial data to detect shifts in cross-scale spatial state variable connectivity (Zurlini et al., 2014).

Major advantages of unknown/unlimited metrics include their flexibility and the fact that three have been tested for EWI applications (Fisher Information, Discontinuity Analysis, Conditional Probability Analysis; Fig. 1). Additionally, these metrics can consider an unlimited number of state variables and combinations of data types (except for Discontinuity Analysis and Conditional Probability Analysis—see below; Fig. 1), and they requirement of little to no a priori system knowledge (Mayer et al., 2007; Tian et al., 2008). Some of these metrics are also capable of significance tests or information theoretic model selection (e.g., Detrended Correspondence Analysis, Detrended Canonical Correspondence Analysis, Sequential T-test Analysis of Regime Shifts, Redundancy Analysis-distance-based Moran's Eigenvector Maps/Asymmetric Eigenvector Maps; Rodionov and Overland, 2005), but unlike known/limited metrics, they do not estimate coefficients, meaning significance tests for unknown/unlimited metrics may produce less specific conclusions than other approaches (Rodionov, 2004; Baho et al., 2014). However, the ability to include unlimited state variables may lead to including extraneous variables that could in turn lead to spurious regime shift detections (Sundstrom et al., 2012). Also, because these metrics do not require input state variables to be drivers or to interact, they provide little information on the directionality or relative importance of state variables regarding regime shifts (Vance et al., 2015).

Any Variable Type

Fisher Information

Fisher Information (FI) is a tested EWI metric, and previous applications demonstrate its utility for early warning detection, regime shift detection, and land management decisions (González-Mejía et al., 2015; Eason et al., 2016; Sundstrom et al., 2017). FI is a measure of the amount of information surrounding an unknown parameter that is obtainable by observation (Fisher, 1922; Karunanithi et al., 2008). It is rooted in statistical estimation theory and has been applied in variety of disciplines ranging from quantum mechanics to ecosystem dynamics (Fath and Cabezas, 2004; Pawlowski et al., 2005; Mayer et al., 2007; Frieden and Gatenby, 2010). FI was recently adapted to assess changes in system behavior and detect regime shifts in complex ecological and social ecological systems (Fath et al., 2003; Karunanithi et al., 2011; Eason and Garmestani, 2012; González-Mejía et al., 2014; Vance et al., 2015; Sundstrom et al., 2017). As a measure of overall system order, FI defines regimes as steady or increasing order and regime shifts as sudden losses of order (Mayer et al., 2007; Eason et al., 2014). Losses of order occur when state variables exceed their typical range of variability (Spanbauer et al., 2014; Eason et al., 2016). In addition to advantages shared with other unknown/unlimited metrics, FI can detect regime shifts and early warnings regardless of resolution or length of the data set (Spanbauer et al., 2014; Eason et al., 2016). For example, Spanbauer et al. (2014) applied FI to a time series dataset on over 100 species of freshwater diatoms across > 7 000-yr period and found evidence of long-term instability preceding a regime shift in community structure. Although FI has primarily been used to assess temporal dynamics, Sundstrom et al. (2017) also used this method to detect regime shifts in space (i.e., spatial regime boundaries) in terrestrial and aquatic community data. Researchers have used FI with other approaches including the variance index (Carpenter and Brock, 2006; Sundstrom et al., 2017) and discontinuity analysis (Spanbauer et al., 2016).

Sequential T-Test Analysis of Regime Shifts

Sequential T-Test Analysis of Regime Shifts (STARS) was initially proposed by Rodionov (2004) as a method for testing for the occurrence of climatic regime shifts. STARS can provide early warning indicators of a regime shift via formal statistical significance tests by using a sequential data processing technique that allows for exploratory analysis that is not dependent on a priori hypothesis for locating regime shifts (Rodionov, 2004). STARS has been applied to a range of time series data beyond climate, including invertebrate and vertebrate community composition data (Tian et al., 2008; Chiba et al., 2009; Wood and Austin, 2009; Kirkman et al., 2015), snowpack characteristics (Irannezhad et al., 2015), streamflow (Johnston and Shmagin, 2008), sea surface temperature (Friedland and Hare, 2007), and thermohaline characteristics (Matić et al., 2011). This method works well in collaboration with variable reduction techniques such as Principal Components Analysis, allowing for the inclusion of a large range of climatic, environmental, and ecological data categories (McQuatters-Gollop and Vermaat, 2011).

Detrended Correspondence Analysis and Detrended Canonical Correspondence Analysis

Detrended correspondence analysis (DCA) and detrended canonical correspondence analysis (DCCA) are two multivariate ordination methods typically used on sparse ecological data (Ter Braak, 1986), often where ecological community assemblage data on species with normal distributions with respect to environmental gradients need to be detrended (remove arch effects; Hill and Gauch Jr., 1980). DCA and DCCA have been used as regime shift detection methods by searching for flickering, skewness, and autocorrelation of variance over time in community or assemblage diversity and structure (Carstensen et al., 2013). For instance, by using a single ordinated axis, DCA identified a livestock grazing threshold gradient and possible regime shift on rangeland plant communities (Sasaki et al., 2008), and DCCA has been used to estimate historic diatom Beta diversity (Hobbs et al., 2010; Liu et al., 2013). DCCA and DCA may be less reliable in detecting changes in systems if the response variable does not follow a Gaussian distribution (Ter Braak, 1986).

Redundancy Analysis–Distance-Based Moran's Eigenvector Maps/Asymmetric Eigenvector Maps

Redundancy Analysis (RDA)–distance-based Moran's Eigenvector Maps/Asymmetric Eigenvector Maps (dbMEM/AEM) is a proposed EWI metric that detects regime shifts and changes in ecological structure by identifying ecological patterns at different spatial or temporal scales; that is, it disentangles decadal, interannual, seasonal, and intraseasonal patterns in time series or continental, regional, and local patterns in data (Borcard and Legendre, 2002; Borcard et al., 2004; Angeler et al., 2009). A refinement of the principal coordinate of neighbor matrix approach, this metric instead uses RDA and models space or time with a dbMEM or dbAEM approach (Dray et al., 2006; Angeler et al., 2009). Rather than using spatial coordinates or a linear time vector directly, dbMEM and AEM carry out a Fourier transformation to spectrally decompose the spatial/temporal relationships among data points into orthogonal eigenfunctions. The resulting functions look like sine waves (or distorted sine waves if the sampling is irregular) of distinct frequencies that are then used as predictor variables in the RDA (Angeler et al., 2010). The number and structure of predictor variables obtained for analysis depends on the length/spatial extent and resolution/grain of the underlying data set. dbMEM differs from AEM in that the latter includes a linear vector in addition to the sine waves, which allows modeling unidirectional processes in time and space (e.g., hydrological flow in streams; Baho et al., 2014; Göthe et al., 2014). The RDA-dbMEM/AEM methods uses rigorous permutation testing, allowing for the determination of robust patterns and numerical assessment of the relative importance of patterns detected at each scale using the amount of adjusted variance explained. This metric has been used in both spatial and temporal contexts with data from lakes and streams (Angeler et al., 2014), marine systems (e.g., Angeler et al., 2014), ancient aquatic systems (Spanbauer et al., 2014), and terrestrial ecosystems (e.g., Widenfalk et al., 2016). These analyses often focus on assessing the organization of the complex behavior and resilience of these systems and their application in management (Angeler and Allen, 2016).

Continuous Variables of the Same Type

Discontinuity Analysis

Discontinuity analysis (DA) is a method developed to objectively identify discontinuities, or scale breaks, in rank-ordered data, and it has been tested as an EWI metric (Allen and Holling, 2008; Sundstrom et al., 2012; Nash et al., 2014; Spanbauer et al., 2016). DA arises from ecological theory that posits ecosystems are multiscaled and hierarchical as a result of structuring processes operating over discrete ranges of spatial and temporal scales (Allen and Starr, 1982; Holling, 1992). Both ecological structure and the species that interact with that structure are scaled in the sense that they function within a limited and particular range of spatial and temporal scales (Allen and Holling, 2008). Animal body masses, which are highly allometric with life-history traits, fall into size classes detectable by DA and can be used as a proxy for the complex spatial and temporal scales of ecological structure and structuring processes (Nash et al., 2014). Changes in body mass size classes in a system over time or space can therefore suggest changes in ecological regimes when regime shifts represent shifts in basic ecological structuring processes (Peterson et al., 1998). For example, used in conjunction with constrained hierarchical clustering, DA detected early warnings of regime shifts in paleodiatom data in freshwater lakes by identifying shifts in the number and location of diatom body mass discontinuities (Spanbauer et al., 2016). DA also detected simplified fish size classes in degraded coral reefs compared with healthier reefs (Nash et al., 2013).

Explicitly Spatial Variables

Conditional Probability Analysis

Conditional Probability Analysis (CPA) uses explicitly spatial data to detect regime shifts by assessing changes in spatial cross-scale land use–land cover connectivity (Zurlini et al., 2014). Using multiple spatial data layers, it calculates proportional land use–land cover (Pc) and connectivity (i.e., adjacency; Pcc) within moving spatial windows of various sizes. As Pc of a given land use–land cover type increases, Pcc increases steadily until a threshold point is breached. At this threshold, a regime shift occurs: as a new land use–land cover regime spreads, Pc abruptly increases exponentially, and Pcc increases much more slowly. In the single study we found using CPA, the authors detected an early warning of a regime shift toward desertification as a result of increased agricultural land connectivity in an urban-rural region of southern Italy (Zurlini et al., 2014).

Discussion

The rangeland discipline has one of the longest histories of using large-scale rangeland inventories and analyses to influence major land management decisions and avoid alternative ecological regimes with less ecosystem service potential (West, 2003). In North America, the first well-coordinated national inventory of terrestrial resources occurred in the United States in 1934 to address concerns over ecological transformations due to soil erosion (National Erosion Reconnaissance Survey). In the decades following, US land management agencies have launched multiple inventory frameworks aimed at maintaining favorable conditions and preventing deleterious regime shifts such as monitoring range quality, estimating degree of rangeland degradation, maintaining so-called climax communities, and tracking the degree of invasion by exotic species (West, 2003). But although monitoring efforts have been successful at identifying ecosystem changes after their occurrence, they often rely on subjective expert opinion or system-specific knowledge applied after the fact, thereby removing the ability to predict surprises inevitable in ecological systems (Twidwell et al., 2013).

The early warning and regime shift detection metrics we review are meant to avoid problems associated with subjectivity and system-specific knowledge requirements. These metrics are often specifically designed to predict surprise and can be applied to presently available rangeland monitoring inventories to directly answer rangeland management and state-transition concerns in a spatially explicit manner. While EWI metrics have not undergone robust experimental evaluation in ecology and even less in the rangeland discipline (Table 2), many robust multivariate rangeland datasets have potential for testing and applying the early warning indicators that can be applied to multivariate data (e.g., the Natural Resources Conservation Service's "Natural Resources Inventory," the US Forest Service's "Forest Inventory and Analysis Program," the US Department of Agriculture's Animal and Plant Health Inspection Service's "Mormon Cricket/Grasshopper Assessment Program"; USDA NRCS, 2015; USDA Forest Service, 2018; USDA APHIS, 2018). For instance, the generalizability of unknown/unlimited metrics such as Fisher Information or Sequential T-test Analysis of Regime Shifts makes them amenable for use in surveillance monitoring frameworks that collect broad swathes of data of various types, and any state variable could be of interest (Hutto and Belote, 2013). Additionally, some unknown/unlimited metrics like RDA-dbMEM/AEM and Discontinuity Analysis have the potential to identify regime shifts and early warning while also estimating the complexity and resilience of rangelands—thereby providing more detailed information on the state of the system and potentially how close or far it is from a regime shift. Conversely, sites with long-term monitoring (e.g., Long-Term Ecological Research [LTER] sites, U.S. Department of Defense lands, or individual properties) or where long-term data might be available in the future, and where the drivers are known (e.g., percent cover of woody plants at Konza Prairie LTER, bare ground at Jornada Basin LTER; Jornada Basin LTER, 2018; Konza Prairie LTER, 2018), known/limited metrics have high potential for early warning applications, depending on how data were collected: for instance, fitted values for percent bare ground at Jornada Basin flickering outside "typical" range of variability or consistently moving toward the boundaries of the typical range of variability could represent early warnings of a state transition (Solow and Beet, 2005; Dakos et al., 2012; Ives and Dakos, 2012). Similarly, EWI metrics requiring hypothesized regime shift locations (e.g., Average Standard Deviates, Intervention Analysis/Autoregressive Moving Averages) can be used in a post-hoc manner with long-term data, and they could also potentially be turned to produce early warnings by sequentially hypothesizing regime shifts in time series data. EWI metrics can also be used to detect regime shifts in spatial rangeland datasets (i.e., as has been assessed with Fisher Information for breeding bird data; Sundstrom et al., 2017).

The new concept of spatial regimes brings together early warning, regime shift, and state-transition theories by identifying where ecological regime shifts/state-transitions are taking place in space and time. Derived from regime shift and alternative state theory, spatial regimes are defined as spatially explicit ecological systems maintained by feedback mechanisms that exhibit self-similarity in structure and composition within their boundaries (Allen et al., 2016; Sundstrom et al., 2017). The abundance of spatial data for rangelands (e.g., remotely sensed vegetation indices, fire history data, land use-land cover data), the geographic breadth of monitoring sites (e.g., the NRCS Natural Resources Inventory's sites distributed throughout private agricultural lands across the United States), and the geographic site-descriptive goals of many rangeland initiatives (e.g., Ecological Site Descriptions) suggest high potential for applying the spatial regime concept in conjunction with EWI metrics in rangelands. For instance, we report only a single article using an EWI metric in a spatial regime context (Sundstrom et al., 2017) and none in rangelands (Table 2), but other EWI metrics with similar approaches to Fisher Information (e.g., Sequential T-test Analysis of Regime Shifts, Discontinuity Analysis) could also be used for spatial regime detection on large-scale (e.g., the US Geological Survey's "North American Breeding Bird Survey") or local-scale (e.g., georeferenced LTER site) datasets. Likewise, CPA, as a tested EWI metric that requires explicitly spatial data, could potentially be used to detect spatial regimes via cross-scale connectivity in remotely sensed rangeland data, searching for early warnings in loss of rangeland heterogeneity, for signs of fragmentation, or for signs of over-connectedness and rigidity traps (Fuhlendorf and Engle, 2001; Hobbs et al., 2008; Zurlini et al., 2014; Peters et al., 2015).

Ignoring the interaction between space and time when searching for patterns indicating early warnings and regime shifts can lead to ecological misinterpretations of underlying structure of state variables (Nash et al., 2014; Baho et al., 2015). For instance, temporal early warnings of regime shifts in yeast populations were found to be suppressed in systems with high levels of connectivity, suggesting that EWI performance is jeopardized by ignoring integrated spatial-temporal components (Dai, 2013). To incorporate interactions between scale-specific spatial and temporal processes into early warning and regime shift modeling, approaches such as spatial/temporal eigenfunction analyses (e.g., the RDA-dbMEM/AEM metric reviewed above; Blanchet et al., 2008) have arisen to identify characteristic spatial and temporal scales at which processes act to structure the distribution of species in a community (Dray et al., 2006, 2012; Peres-Neto and Legendre, 2010; Smith and Lundholm, 2010). Often spatial/temporal eigenvectors are combined with canonical ordination techniques or other multivariate community models to account for spatial-temporal patterns in community data, thereby offering increased performance for detecting regime shifts in systems where there is strong coupling of spatial and temporal variation at multiple scales (Legendre and Gauthier, 2014). Although many EWI metrics do not, spatial/temporal eigenfunction analyses often require large-scale and/or long-term data relative to the community of interest, making the intensive monitoring data collected by rangeland scientists and managers imperative for using these EWI metrics and disentangling spatiotemporal scaling issues.

To identify situations when EWI metrics would be useful and appropriate, primary considerations relate to system characteristics, research questions, data availability, and social or policy concerns (Table 3; Fig. 1). Although EWI metrics often require little a priori knowledge of systems, some system-specific information can help decide which or if EWI metrics are appropriate (Lade et al., 2013; Mantua, 2004). For instance, the presence of hysteresis or thresholds may increase the cost of restoration, making detecting early warnings of regime shifts the more palatable option (Suding and Hobbs, 2009). Choosing when to use a metric will also depend on the research goal (e.g., active experimentation on regime shifts or passive monitoring), and data availability (Sample size, is it spatial? Is it temporal?; Fig. 1). In addition to ecological and statistical considerations, social or policy concerns can influence when or if to use EWI metrics. EWI metrics can provide evidence, and even estimates of confidence, to support the presence or absence of thresholds and regime shifts (Rodionov, 2004; Ives and Dakos, 2012). This can be used to inform policymakers and provide decision-making tools for managers. For example, an early warning signal could represent a policy "trigger point" for initiating management or restoration (Lindenmayer et al., 2013; Eason et al., 2016). Data constraints (e.g., time-series and spatial data with sufficient resolution to cover relevant ecological scales are usually absent), the lack of detailed knowledge for many traits, organisms, and processes represent a general limitation to the application of regime shift detection in rangelands. However, several extant national or regional monitoring programs may provide data for testing the regime shift indicators reviewed in this paper. Several experimental monitoring initiatives (Borer et al., 2014; Nutrient Network, 2018) are underway to overcome this limitation.

Management Implications

Early warning metrics and regime shift detection provide practical tools to assess rangeland vulnerability and resilience in the face of rapid environmental change. Here, we draw upon three examples where the scientific exploration of these metrics can benefit core pursuits in the rangeland discipline. We encourage readers to read the full articles to obtain more information.

Example 1: Earlier detection of rangelands in transition

Decades of field monitoring data have been collected in rangelands with the hope of providing earlier signals of rangeland transitions. Roberts et al. (in review) identify spatial regimes in actual grassland monitoring data (Fig. 2A) and then demonstrate the potential to use an EWI to detect, via simulation of future field monitoring, 1) the spatial scale at which a new shrubland regime emerged and expanded over time (Fig. 2B), and 2) the potential to detect earlier warning of transitions via flickering (Fig. 2C), an established early warning signal (Dakos et al., 2012). The study drew from actual field monitoring data collected across a 4-km transect at the Niobrara Valley Preserve, Nebraska. Sampling of community composition and structure identified the presence of smooth sumac (*Rhus glabra*) within an expansive Sandhills grassland prairie, but constrained hierarchical clustering did not identify the patch with sumac as one of the current spatial regimes present at the site. A simulation was conducted over time, using known assembly rules derived from previous research, to test the potential for future field monitoring to be

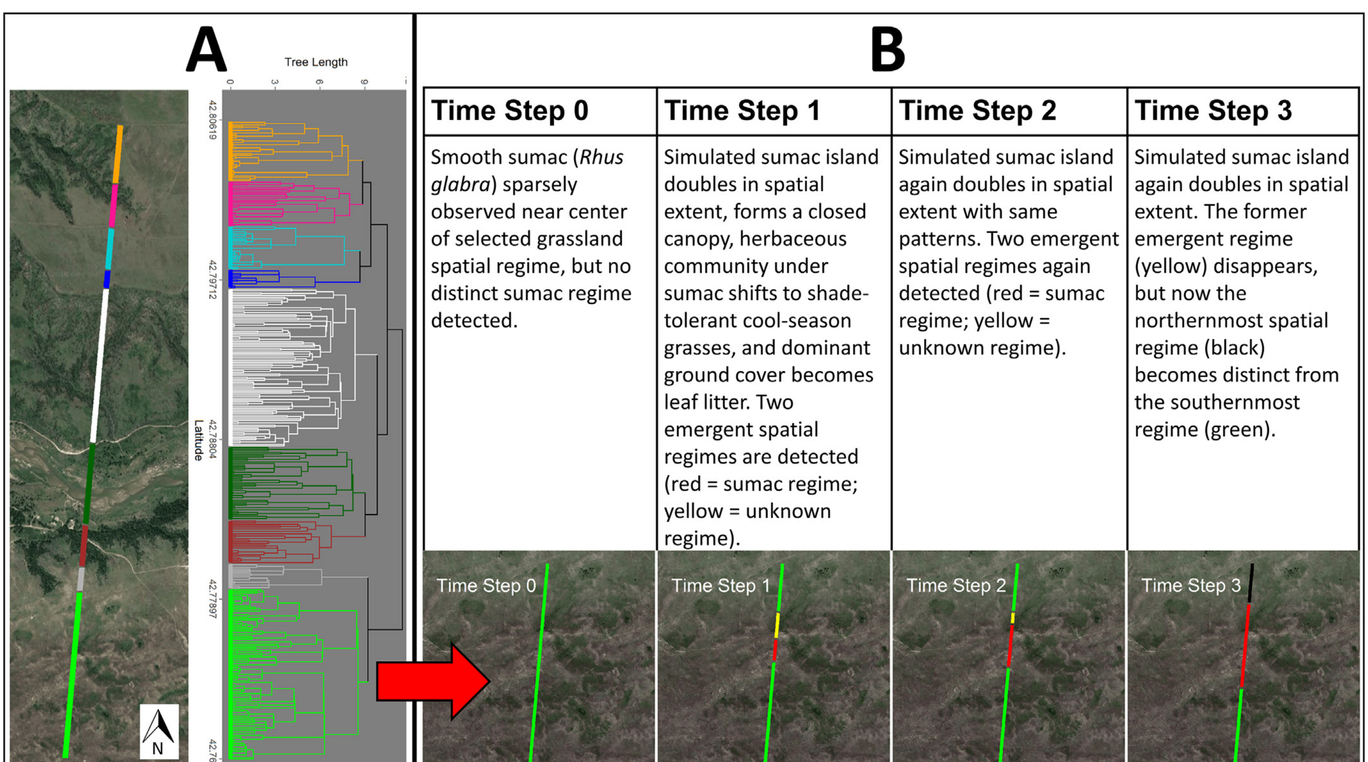

Figure 2. The emergence of new states, and the potential to avoid collapses in existing states, has been a preeminent focus of rangeland ecology and management. Roberts et al. (in review) incorporate the spatial regimes concept into field monitoring data collected along a 4 km transect at the Niobrara Valley Preserve, Nebraska, USA. This study identifies (A) the existing number and types of spatial regimes at the site, (B) the potential for using an early warning indicator in conjunction with the spatial regime concept to identify, via simulation of future field monitoring (table of assembly rules for each time step), the location and spatial scale at which a shrubland regime emerged and the emergence of novel/unknown regimes, at the cost to the previously dominant grassland regime, over time.

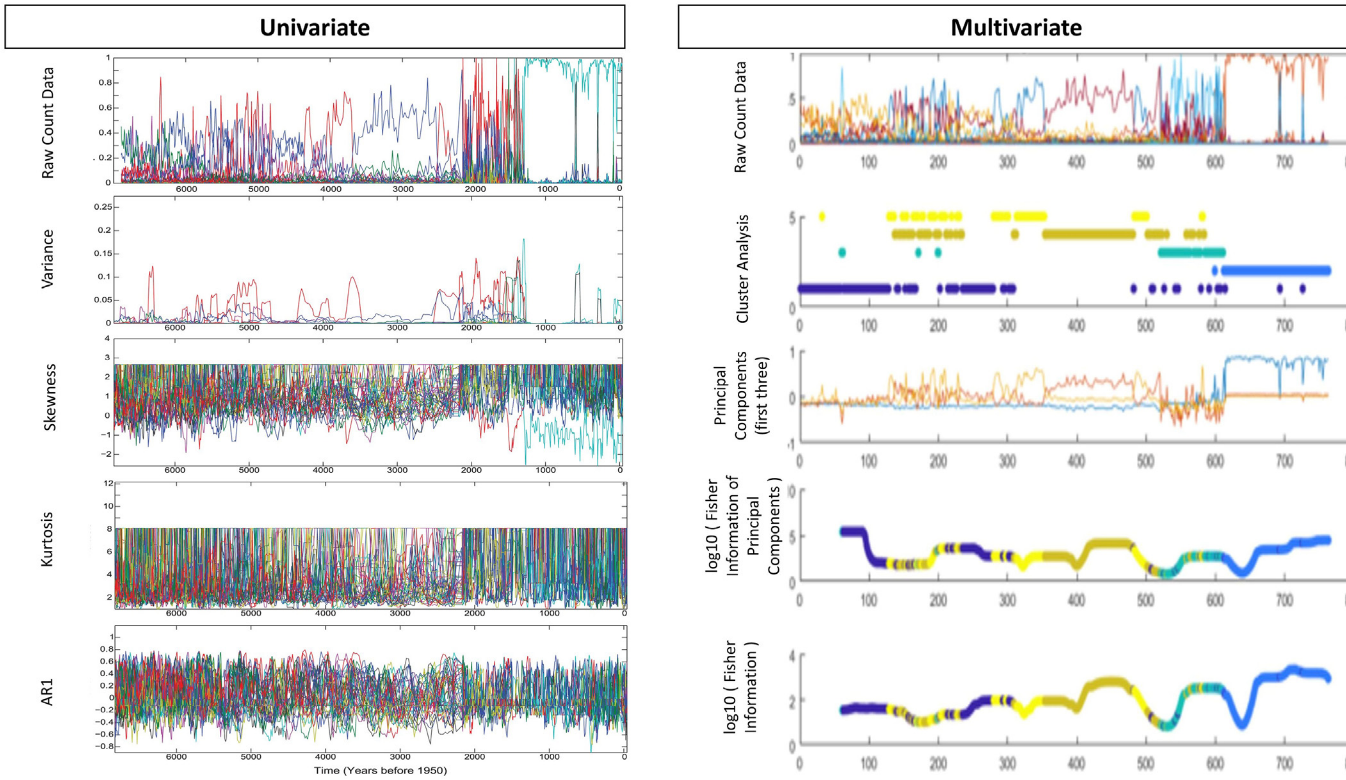

Figure 3. Integrative metrics that accommodate multivariate data are being explored to assess their potential utility to detect early warning and regime change in complex adaptive systems. Spanbaeur et al. (2014) compare various multivariate and univariate indicators using paleo-diatom data. Several populations of species experienced increased variability in this study, but conflicting patterns make it difficult to operationalize univariate statistics to characterize the behavior of this complex, multivariate system. Similar trends and observations might be expected in rangelands, but research has been limited, to date, to test these concepts and to assess their practical utility to rangeland managers.

paired with the clustering method in order to detect the emergence of a sumac-dominant regime over time. A major implication from this study is that early warning indicators can be used to identify the location and scale of shifting spatial regime boundaries, which could serve as "trigger points" for enacting management actions or changing policies in an adaptive monitoring/management framework (Lindenmayer et al., 2013).

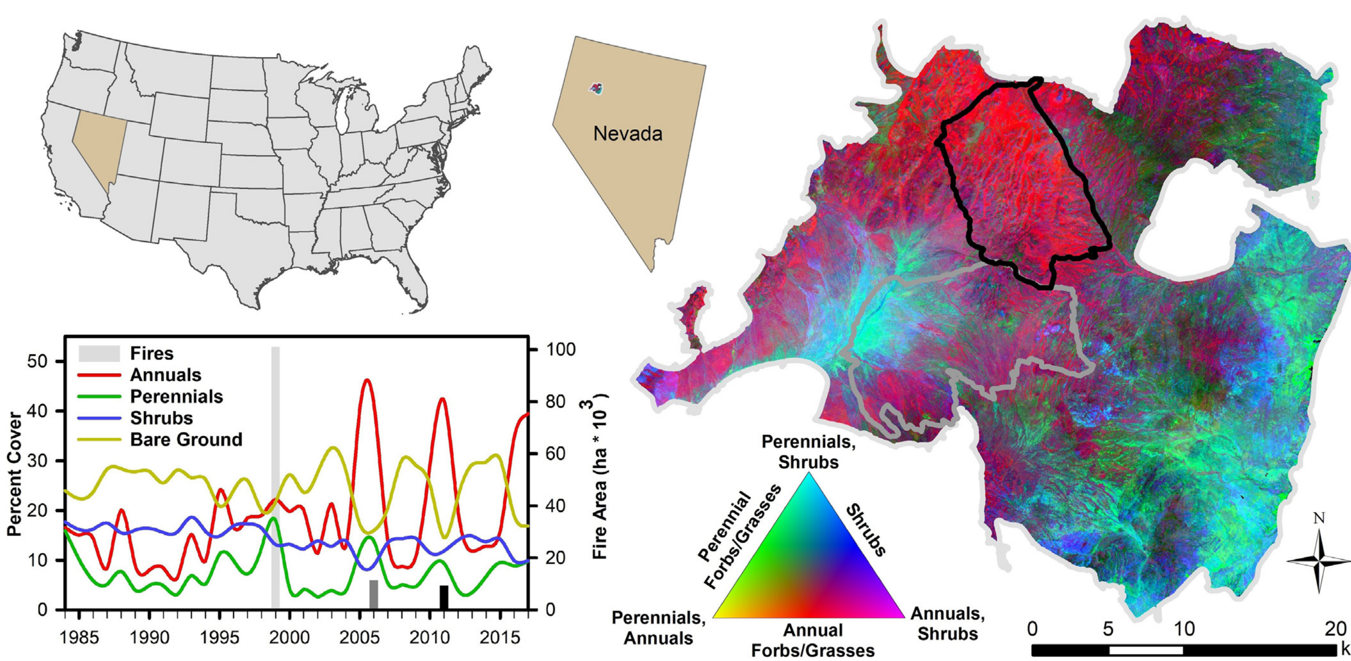

Figure 4. Future availability of remote sensing products with high spatiotemporal resolution has great potential to be incorporated into multivariate metrics used to detect early warning signals and regime shifts. The bottom left panel shows trends in annual percent cover of annual forbs/grasses, perennial forbs/grasses, shrubs, and bare ground from 1984–2017 within an area in Nevada, USA that is experiencing cheatgrass (*Bromus tectorum*) invasion. Bars denote the area of the Dun Glenn fire and subsequent smaller scale fires that burned within the original fire perimeter. The image to the right is a single year of the remotely-sensed data for the area of the Dun Glenn and subsequent fires for a single year. The triangle below the image indicates which colors correspond with a continuum of plant functional type percentages on the remotely-sensed image.

Example 2: Preparing management for system-level change

A fundamental problem in the development of leading indicators is that the performance of univariate indicators have been inconsistent, with high uncertainty surrounding their potential to predict future regime change (Brock and Carpenter, 2012). Traditional (univariate) leading indicators also typically require the critical variables driving transitions to be known a priori, which is unrealistic in a future characterized by novelty and uncertainty. Spanbauer et al. (2014) assess some of the multivariate indicators featured in this review and compare their utility to univariate indicators (Fig. 3). This paper reveals a general problem all-too familiar to rangeland scientists and managers; that is, monitoring and management focused on a particular species or state variable of interest effectively masks community-level analyses from detecting system-level change. This paper shows that acting based on traditional univariate indicators becomes infeasible given the inconsistent signals and lack of spatial boundary detection needed to differentiate patterns among multiple populations of interest. In contrast, the authors conclude that more integrated measures that accommodate multivariate data have the potential to better reflect the reality of complex and adaptive ecological systems, like rangelands, and how to operationalize spatially explicit signals of regime change.

Example 3: Advances in rangeland monitoring and application

Investments in technological innovation and computer processing is leading to rapid growth in strategic targeting tools that makes huge amounts of information and data readily accessible for rangeland science and planning. For example, utilizing robust ground level measurements, machine learning, and high performance cloud-based computing, Jones et al. (in review) produce annual maps with historical (1984–2017), continuous cover data (0–100%) of plant functional groups for US rangelands (Fig. 4). The data product removes the barrier of single class, arbitrarily delineated categorical data (e.g., where a pixel, landscape, or region is classified solely as grassland, shrubland, or tree), which removes information necessary to explore the potential utility of the early warning and regime shift metrics featured in this review. In addition, by utilizing frameworks that do not require or utilize a priori knowledge of states but instead focuses on transitions that are detectable and measurable, it is possible to identify spatial risks or vulnerabilities to transitions and then concentrate management activities where it is most needed and will be most effective. The coupling of these data and frameworks will prompt a shift from the static inventory and state mapping paradigm (Steele et al., 2012) within rangeland ecology to one of variability and transitions (Fuhlendorf and Engle, 2001; Twidwell et al., 2013).

Overall, the EWI metrics we review and, more broadly, the early warning/spatial regime paradigm represent quantitative, more objective decision-making tools for rangeland management in the face of ecological uncertainty (Lindenmayer and Likens, 2009; Allen et al., 2017). Traditional inventory and monitoring efforts are not designed with the spatial specificity needed to provide indicators of sudden change in many rangeland systems; however, statistical theory is advancing to be able to better incorporate broad-scale monitoring and inventory data for purposes of early warning and regime shift detection. Rangeland science is in a solid position to experimentally assess and integrate these metrics into monitoring and management, given the discipline's long-term focus on broad-scale monitoring and inventory data. Moving forward, the quantitative metrics reviewed herein could fit within joint efforts to couple adaptive management and monitoring as part of a co-learning process—where the utility of the metrics are tested and the monitoring necessary for their application is critiqued while also using an iterative decision-making process to guide their adoption.

Acknowledgments

This project was supported by funds from the Department of Defense Strategic Environmental Research and Development Program (W912HQ-15-C-0018), Nebraska Game & Parks Commission (W-125-R-1), the August T. Larsson Foundation of the Swedish University of Agricultural Sciences, the USDA NRCS Working Lands for Wildlife, Sage Grouse Initiative, Wildlife Conservation Effects Assessment Project, and the University of Nebraska's Institute of Agriculture and Natural Resources. The Nature Conservancy also provided partial support for this work through the Nebraska Chapter's J.E. Weaver Competitive Grants Program. We are also thankful for feedback provided by international partners from the Complexity Science Working Group, hosted at the University of Nebraska, in particular, we thank Hannah E. Birge for advice and assistance in creating the glossary table. The Nebraska Cooperative Fish and Wildlife Research Unit is jointly supported by a cooperative agreement between the US Geological Survey, the Nebraska Game and Parks Commission, the University of Nebraska–Lincoln, the US Fish and Wildlife Service, and the Wildlife Management Institute. Any use of trade, firm, or product names is for descriptive purposes only and does not imply endorsement by the US Government. The views expressed in this paper are those of the authors and do not represent the views or policies of the US Environmental Protection Agency.

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